On Ordered Weighted Reference Point Model for Multi-attribute Procurement Auctions

Bartosz Kozłowski and Włodzimierz Ogryczak

Warsaw University of Technology,
Institute of Control & Computation Engineering, 00-665 Warsaw, Poland
{b.kozlowski,w.ogryczak}@elka.pw.edu.pl

Abstract. Multi-attribute auctions (also called multidimensional auctions) facilitate negotiations based on multiple attributes, thus escape from the standard price-only domain into a rich multidimensional domain that can comprise additional attributes like e.g. guarantee conditions or quality. Most multi-attribute preference models used in auction mechanisms are based on a ranking derived from weighted sum. Recently, the Reference Point Method (RPM) approach has been applied to express the multi-attribute preference models within the auction mechanisms allowing to overcome the weighted sum drawbacks. The Ordered Weighted RPM model enables us to introduce importance weights to affect achievements importance by rescaling their measures accordingly within the distribution of all achievements. The concept presented and discussed in this paper in the context of procurement auctions takes advantage of the so-called Weighted Ordered Weighted Average (WOWA) aggregations of the partial achievements.

Keywords: multi-attribute auction, ordered weighted average, reference point method.

1 Introduction

Procurement refers to the process of obtaining goods and services required by the firm. It may be considered the acquisition of appropriate goods or services at the best possible total cost while complying with the needs of the buyer. Many types of businesses, public institutions in particular, very often define procurement processes with intention to promote fair and open competition for their business and minimize exposure to secret agreements and fraud. For this reason a competitive bidding is widely deployed in procurement. Competitive bidding is the process by which multiple suppliers submit competing offers to supply the goods or services requested by the firm, which then awards business to the supplier(s) based on these offers. The emergence of Internet-based communication between firms has enabled them to effectively organize competitive bidding events. These may be either "one shot" or "dynamic". The latter allows several rounds of bidding thus forming the so-called auction process. An auction format is simply a set of predefined rules outlining how bids will be submitted and how

P. Jędrzejowicz et al. (Eds.): ICCCI 2011, Part I, LNCS 6922, pp. 294–303, 2011.

the winner and payments will be subsequently determined based on the bids [27]. Based on bids and asks placed by market participants, resource allocation and prices are determined. In electronic commerce transactions, auctions are conducted by software agents that negotiate on behalf of buyers and sellers [2,4,9]. The various auction protocols include English, First-price Sealed Bid, Dutch, Vickrey and others [11]. The procurement auction is a reverse auction, i.e. it is a type of auction in which the roles of buyers and sellers are reversed. In an ordinary auction (also known as a forward auction), buyers compete to obtain a good or service. Typically, as a result of this competition, the price increases during the auction. In a reverse auction, sellers compete to provide the buyer with their good or service. Typically, as a result of this type of competition, price decreases during the auction. Reverse auction is a strategy used by many purchasing and supply management organizations for spend management, as part of strategic sourcing and overall supply management activities.

One of the key challenges of current day electronic procurement systems is to enable procurement decisions overcome a limitation to a single attribute such as cost. As a result, multi-attribute procurement has gained on importance and became popular research direction. Multi-attribute auctions allow negotiations to involve multiple attributes, i.e. they overcome the limitation of single dimension of the price and expand to other attributes like e.g. quality or reputation [21]. Usually, buyer reveals her / his preferences on the good / service to be purchased. Following that sellers compete on all attributes to win the auction. Multi-attribute auctions require several key components to automate the process [4]: a preference model to let the buyer express his preferences, a multicriteria aggregation model to let the buyer agent select the best offer, a decision making component to let the buyer agent formulate her / his asks. Buyer's preferences are expressed by defining a set of relevant attributes, the domain of each attribute, and criteria which are evaluation functions that allocate a score for every possible values of a relevant attribute. Most multicriteria aggregation models used in multi-attribute negotiations are scoring functions based on a weighted sum [5,6,13,22]. It is well-known, however, that the weighted sum, which is the simplest multicriteria aggregation model, suffers from several drawbacks. This is essentially due to the fact that the weighted sum is a totally compensatory aggregation model with trade-off weights which are difficult to obtain and to interpret in the case of more than two attributes [26]. In our context, a very bad value on a criterion can be compensated by a series of good values on other criteria. Such a bid could obtain a weighted sum similar to a bid with rather good scores on all criteria, while in many cases, the latter would be preferred. Moreover, the selections are unstable in the sense slight variations on the weights may change dramatically the choice of the best bid. Finally, it can be shown that some of the non-dominated solutions, called non-supported, cannot be obtained as the best proposal using the weighted sum for any possible choice of weights. This is a very severe drawback since these non-supported solutions, whose potential interest is the same as the other non-dominated solutions, are rejected only for technical reasons. In order to address these shortcomings, Bellosta et al. [3] proposed the use of an alternative multicriteria model for the buyer's preferences, based on the Reference Point Method [25]. There was proposed a complete reverse auction mechanism based on this model where buyer's asks specify the values required on the attributes of the item at each step of the auction process. This mechanism provides more control to the buyer agent over the bidding process than with the weighted sum model. In this approach, preference information and relative importance of criteria is not expressed in terms of weights, but more directly in terms of required values on the criteria. Moreover, while in the weighted sum, any non-dominated solution can be obtained as the best proposal.

This paper is organized as follows. Section 2 recalls basic concepts from Multicriteria Decision Analysis (MCDA). Section 3 analyses related work [3] introducing to the Reference Point Method (RPM) based multi-attribute auction mechanism where both the preference model and the multicriteria aggregation model used by the buyer agent are based on the RPM. Section 4 presents Weighted Ordered Weighted Averaging (WOWA) extension of the RPM model thus allowing to introduce the importance weighting of attributes into the buyer preference model and the corresponding procedure for the best offer selection. This section is followed by a concluding section.

2 MCDA Concepts in Procurement Auctioning Context

A single step (round) in multi-attribute procurement auction corresponds to a special case of multicriteria problem. There is a known set $\mathcal{D}$ of A offers $\mathbf{x}$ ($\mathbf{x} \in \mathcal{D}$). Every offer is characterized by a set of m attributes undergoing evaluation. Therefore, every offer $\mathbf{x}^a$ has a corresponding, vector of evaluations $\mathbf{y}^a = y_1^a, ..., y_I^a$ where y_i^a denotes evaluation corresponding to i-th attribute for a-th offer. This may be presented as in Tab. 1.

The buyer aims to select such an offer for which its corresponding evaluation is better than evaluations of other offers. In case when the evaluation space is multi-attribute ($m > 1$) judging which of the two given offers is better than the other is usually not straight-forward. In general, preferences revealed by the buyer may be expressed as a two argument relation (preference relation). This relation is a certain set of pairs of evaluations, for which one can say "this one is better than the other".

Let us take a sample evaluation $\bar{\mathbf{y}}$. If $\bar{\mathbf{y}}$ is better than all other evaluations then $\bar{\mathbf{y}}$ is called the greatest and the corresponding offer is the best. If there is no such an evaluation that it is better than $\bar{\mathbf{y}}$ then $\bar{\mathbf{y}}$ is called maximal. If $\bar{\mathbf{y}}$ is not better than any other evaluation then $\bar{\mathbf{y}}$ is called minimal. If $\bar{\mathbf{y}}$ is worse than all other evaluations then it is called the least and the corresponding offer is the worse.

The maximal element is called non-dominated and the greatest element is called dominating. Every minimal element is dominated by some element(s) and the least element is dominated by all other elements. In such case the preference relation is called a (strong) dominance relation if there exists the greatest element with respect to this relation. Relation is called a (weak) dominance relation if there is a maximal element with respect to this relation.

Table 1. Partial evaluations

Offers	Evaluations	Attributes					
		f_1	f_2	...	f_i	...	f_m
		Partial evaluations					
$\mathbf{x}^1$	$\mathbf{y}^1$	y_1^1	y_2^1	...	y_i^1	...	y_m^1
$\mathbf{x}^2$	$\mathbf{y}^2$	y_1^2	y_2^2	...	y_i^2	...	y_m^2
...	...	...	...	...	...	...	...
$\mathbf{x}^a$	$\mathbf{y}^a$	y_1^a	y_2^a	...	y_i^a	...	y_m^a
...	...	...	...	...	...	...	...
$\mathbf{x}^A$	$\mathbf{y}^A$	y_1^A	y_2^A	...	y_i^A	...	y_m^A

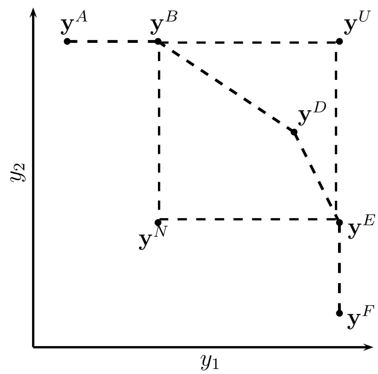

Fig. 1. Basic concepts in MCDA

An offer is called an Optimal Solution (OS) if the corresponding evaluation is dominating in a sense of a defined preference relation. Referring to Fig. 1 one can see that offer $\mathbf{x}^U$ could be an OS as well as all potential offers that could be placed, say, north-east of $\mathbf{x}^U$. However, they are not feasible, there was no seller bidding with such an offer, or even such a combination of evaluations of attributes is not possible. Efficient Solution (ES) is such an offer for which the corresponding evaluation is non-dominated (maximal element in preference relation). According to the preference relation offer $\mathbf{x}^0$ is an ES when there is no other offer in the available such that it is not worse for every attribute and it is better at least for one attribute. If the problem has many non-dominated evaluations (what means many ESs) one could draw a conclusion that model of preferences needs improvement. Big number of ESs does not really support the buyer in choosing the offerent.

Fig. 1 illustrates basic concepts in MCDA. Axes y_1 and y_2 span the space of a two attribute problem. Points $\mathbf{y}^A$, $\mathbf{y}^B$, $\mathbf{y}^D$, $\mathbf{y}^E$, $\mathbf{y}^F$ correspond to evaluation of five arbitrary offers. From these, only evaluations $\mathbf{y}^B$, $\mathbf{y}^D$ and $\mathbf{y}^E$ correspond to ESs. Obviously, offer evaluated with $\mathbf{y}^A$ is worse than offer corresponding to $\mathbf{y}^B$ and offer given $\mathbf{y}^F$ is worse than offer scored with $\mathbf{y}^E$. Evaluation $\mathbf{y}^U$ (that is called the utopia) is a virtual point that is constructed by using best value for each attribute separately. Similarly, evaluation $\mathbf{y}^N$ (that is called the nadir) is constructed by taking the worst value for each attribute (from the ESs set only).

3 The RPM Based Auction Model

In order to specify the procedure used to select the best bid in detail, one needs to assume some multicriteria solution concept well adjusted to the buyer's preferences. This can be achieved with the so-called quasi-satisficing approach proposed and developed mainly by Wierzbicki [25] as the Reference Point Method (RPM). This approach has led to efficient implementations with many successful applications in various domains [12,26]. The RPM is an interactive technique that can be described on the ground of auctioning as follows. The buyer specifies requirements in terms of reference levels for all attributes, i.e., she / he introduces reference values for several individual evaluations. Depending on the specified reference levels, a special Scalarizing Achievement Function (SAF) is built. The SAF may be directly interpreted as expressing utility to be maximized. Maximization of the SAF generates an ES to the multicriteria problem. The computed ES is presented to the buyer as the current solution in a form that allows comparison with the previous ones and modification of the reference levels if necessary.

The SAF can be viewed as two-stage transformation of the original evaluations. First, the strictly monotonic Partial Achievement Functions (PAFs) are built to measure individual performance on each attribute with respect to given reference levels. Having all the evaluations transformed into a uniform scale of individual achievements they are aggregated at the second stage to form a unique scalarization. The RPM is based on the so-called augmented (or regularized) max-min aggregation. Thus, the worst individual achievement is essentially maximized but the optimization process is additionally regularized with the average achievement. The generic SAF takes the following form [25]:

$$S(\mathbf{y}) = \min_{1 \leq i \leq m} \{s_i(y_i)\} + \frac{\varepsilon}{m} \sum_{i=1}^{m} s_i(y_i) \tag{1}$$

where ε is an arbitrary small positive number and $s_i : R \to R$, for $i = 1, 2, \ldots, m$, are the PAFs measuring actual achievement of the individual evaluations y_i with respect to the corresponding reference levels. Let a_i denote the partial achievement for the i-th evaluation ($a_i = s_i(y_i)$) and $\mathbf{a} = (a_1, a_2, \ldots, a_m)$ represent the achievement vector. Various functions s_i provide a wide modeling environment for measuring partial achievements [26]. The basic RPM model is based on a single vector of the reference levels, the aspiration vector $\mathbf{r}^a$ and the Piecewise Linear (PWL) functions s_i.

Real-life applications of the RPM methodology usually deal with more complex PAFs defined with more than one reference point [26]. In particular, the models taking advantage of two reference vectors: vector of aspiration levels $\mathbf{r}^a$ and vector of reservation levels $\mathbf{r}^r$ [12] are used, thus allowing the buyer to specify requirements by introducing acceptable and required values for several evaluations. The PAF s_i can be interpreted then as a measure of the buyer's satisfaction with the current value of evaluation the i-th criterion. It is a strictly increasing function of evaluation y_i with value $a_i = 1$ if $y_i = r_i^a$, and $a_i = 0$ for $y_i = r_i^r$. Various functions can be built meeting those requirements. We use the PWL PAF [18]:

$$s_i(y_i) = \begin{cases} \gamma(y_i - r_i^r)/(r_i^a - r_i^r), & y_i \leq r_i^r \\ (y_i - r_i^r)/(r_i^a - r_i^r), & r_i^r < y_i < r_i^a \\ \alpha(y_i - r_i^a)/(r_i^a - r_i^r) + 1, & y_i \geq r_i^a \end{cases} \tag{2}$$

where α and γ are arbitrarily defined parameters satisfying $0 < \alpha < 1 < \gamma$.

At each round of a reverse auction, the buyer agent collects all the bids, selects the best one as the reference bid for the next round and formulates the counterproposal. The definition of counterproposals is based on the beat-the-quote rule which specifies that any new bid must beat the best bid received at the previous round. In the standard case of one-dimensional (price) auction, this rule can simply be implemented by communicating to the sellers the evaluation of the best current bid augmented by a minimal increment Δ. Sellers are then asked to send new bids whose evaluation is at least as good as this augmented evaluation. The same may be applied to a scalar aggregation function but this would require that sellers know and implement the buyer's evaluation model. As shown in [3] the RPM based auction mechanism satisfies the beat-the-quote rule without revealing the buyer's evaluation model to the sellers. This is achieved through the use of reservation levels set as the best bid's achievements augmented by a minimal increment Δ and communicated to the sellers as the minimal requirements.

In the multi-attribute procurement auction protocol buyer agent gathers information about buyers preferences. These include the value functions and respective aspiration and reservation levels. Additionally, the time of the closing of the auction is set. The buyer agent also specifies an increment used to define counterproposals and time span of a single negotiation round. All this information is sent to seller agents who in reply send initial proposal (or abort their participation). Repeatedly, until the auction ends, after evaluation of all proposals the best seller is marked as active and other sellers are updated with new reservation levels to allow further bidding. The auction ends with success when there is only one seller left in the competition or when the closing time of the auction is reached. The auction end with failure if there is no seller left in the competition.

4 WOWA Extension of the RPM

The crucial properties of the RPM are related to the max-min aggregation of partial achievements while the regularization is only introduced to guarantee the aggregation monotonicity. Unfortunately, the distribution of achievements may make the max-min criterion partially passive when one specific achievement is relatively very small for all the solutions. Maximization of the worst achievement may then leave all other achievements unoptimized. Nevertheless, the selection is then made according to linear aggregation of the regularization term instead of the max-min aggregation, thus destroying the preference model of the RPM [17].

In order to avoid inconsistencies caused by the regularization, the max-min solution may be regularized according to the ordered averaging rules [28]. This is mathematically formalized as follows. Within the space of achievement vectors we introduce map $\Theta = (\theta_1, \ldots, \theta_m)$ which orders the coordinates of achievements vectors in a nonincreasing order, i.e., $\Theta(a_1, \ldots, a_m) = (\theta_1(\mathbf{a}), \theta_2(\mathbf{a}), \ldots, \theta_m(\mathbf{a}))$ iff there exists a permutation τ such that $\theta_i(\mathbf{a}) = a_{\tau(i)}$ for all i and $\theta_1(\mathbf{a}) \geq$

$\theta_2(\mathbf{a}) \geq \ldots \geq \theta_m(\mathbf{a})$. The standard max-min aggregation depends on maximization of $\theta_m(\mathbf{a})$ and it ignores values of $\theta_i(\mathbf{a})$ for $i \leq m-1$. In order to take into account all the achievement values, one needs to maximize the weighted combination of the ordered achievements thus representing the so-called Ordered Weighted Averaging (OWA) aggregation [28]. Note that the weights are then assigned to the specific positions within the ordered achievements rather than to the partial achievements themselves. With the OWA aggregation one gets the following RPM model:

$$\max\{\sum_{i=1}^{m} w_i\theta_i(\mathbf{a}) \ : \ a_i = s_i(f_i(\mathbf{x})) \ \forall \ i, \ \mathbf{x} \in Q \ \} \tag{3}$$

where $w_1 < w_2 < \ldots < w_m$ are positive and strictly increasing weights. Actually, they should be significantly increasing to represent regularization of the max-min order. Note that the standard RPM model with the scalarizing achievement function (1) can be expressed as the OWA model (3) with weights $w_1 = \ldots = w_{m-1} = \varepsilon/m$ and $w_m = 1 + \varepsilon/m$ thus strictly increasing in the case of $m = 2$. Unfortunately, for $m > 2$ it abandons the differences in weighting of the largest achievement, the second largest one etc ($w_1 = \ldots = w_{m-1} = \varepsilon/m$). The OWA RPM model (3) allows one to differentiate all the weights by introducing increasing series (e.g. geometric ones).

Typical RPM models allow weighting of several achievements only by straightforward rescaling of the achievement values. The OWA RPM model enables one to introduce importance weights to affect achievement importance by rescaling accordingly its measure within the distribution of achievements as defined in the so-called Weighted OWA (WOWA) aggregation [23]. Let $\mathbf{w} = (w_1, \ldots, w_m)$ be a vector of preferential (OWA) weights and let $\mathbf{p} = (p_1, \ldots, p_m)$ denote the vector of importance weights ($p_i \geq 0$ for $i = 1, 2, \ldots, m$ as well as $\sum_{i=1}^{m} p_i = 1$). The corresponding Weighted OWA aggregation of achievements $\mathbf{a} = (a_1, \ldots, a_m)$ is defined as follows:

$$A_{\mathbf{w},\mathbf{p}}(\mathbf{a}) = \sum_{i=1}^{m} \omega_i\theta_i(\mathbf{a}), \qquad \omega_i = w^*(\sum_{k\leq i} p_{\tau(k)}) - w^*(\sum_{k<i} p_{\tau(k)}) \tag{4}$$

where w^* is an increasing function that interpolates points $(\frac{i}{m}, \sum_{k\leq i} w_k)$ together with the point (0.0) and τ representing the ordering permutation for $\mathbf{a}$ (i.e. $a_{\tau(i)} = \theta_i(\mathbf{a})$). Moreover, function w^* is required to be a straight line when the point can be interpolated in this way. Due to this requirement, the WOWA aggregation covers the standard weighted mean with weights p_i as a special case of equal preference weights ($w_i = 1/m$ for $i = 1, 2, \ldots, m$). Function w^* can be defined by its generation function

$$g(\xi) = m w_i \quad \text{for} \quad (i-1)/m < \xi \leq i/m, \quad i = 1, 2, \ldots, m \tag{5}$$

with the formula $w^*(\alpha) = \int_0^\alpha g(\xi)\ d\xi$.

Introducing breakpoints $\alpha_i = \sum_{k\leq i} p_{\tau(k)}$ and $\alpha_0 = 0$ allows us to express

$$\omega_i = \int_0^{\alpha_i} g(\xi)\ d\xi - \int_0^{\alpha_{i-1}} g(\xi)\ d\xi = \int_{\alpha_{i-1}}^{\alpha_i} g(\xi)\ d\xi$$

Therefore, the WOWA may be expressed with more direct formula where preferential (OWA) weights w_i are applied to averages of the corresponding portions of ordered achievements (quantile intervals) according to the distribution defined by importance weights p_i [20]:

$$A_{\mathbf{w},\mathbf{p}}(\mathbf{a}) = \sum_{i=1}^{m} w_i m \int_{\frac{i-1}{m}}^{\frac{i}{m}} F_{\mathbf{a}}^{(-1)}(\xi)\ d\xi \tag{6}$$

where $\overline{F}_{\mathbf{a}}^{(-1)}$ is the stepwise function $\overline{F}_{\mathbf{a}}^{(-1)}(\xi) = \theta_i(\mathbf{a})$ for $\beta_{i-1} < \xi \leq \beta_i$. It can also be mathematically formalized as follows. First, we introduce the right-continuous cumulative distribution function (cdf) $F_{\mathbf{a}}(d) = \sum_{i=1}^{m} p_i \delta_i(d)$ where $\delta_i(d) = 1$ if $a_i \leq d$ and 0 otherwise. Next, we introduce the quantile function $F_{\mathbf{a}}^{(-1)} = \inf \{\eta : F_{\mathbf{a}}(\eta) \geq \xi\}$ for $0 < \xi \leq 1$ as the left-continuous inverse of $F_{\mathbf{a}}$, ie., $F_{\mathbf{a}}^{(-1)}(\xi) = \inf \{\eta : F_{\mathbf{a}}(\eta) \geq \xi\}$ for $0 < \xi \leq 1$, and finally $\overline{F}_{\mathbf{a}}^{(-1)}(\xi) = F_{\mathbf{a}}^{(-1)}(1-\xi)$.

Formula (6) defines the WOWA value applying preferential weights w_i to importance weighted averages within quantile intervals. It may be reformulated to use the tail averages which are LP computable. Indeed, one may get the following model [17] for the WOWA RPM with PWL PAFs (2):

$$\max \sum_{k=1}^{m} w'_k z_k \quad \text{s.t.} \quad \begin{array}{ll} z_k = k t_k - m \sum_{i=1}^{m} p_i d_{ik} & \forall\ k \\ \mathbf{x} \in Q,\ y_i = f_i(\mathbf{x}) & \forall\ i \\ a_i \geq t_k - d_{ik},\ d_{ik} \geq 0 & \forall\ i, k \\ a_i \leq \gamma(y_i - r_i^r)/(r_i^a - r_i^r) & \forall\ i \\ a_i \leq (y_i - r_i^r)/(r_i^a - r_i^r) & \forall\ i \\ a_i \leq \alpha(y_i - r_i^a)/(r_i^a - r_i^r) + 1 & \forall\ i \end{array} \tag{7}$$

thus allowing for implementation of the entire WOWA RPM model as an LP expansion of the original problem. Although while using the WOWA RPM aggregation to find out the best bid we are dealing with a finite discrete set of bids and the direct WOWA formula (4) with predefined piecewise linear function w^* can be effectively used.

The WOWA aggregation with positive weights is strictly increasing [17]. Therefore, similar to the standard RPM based auction mechanism [3], the WOWA RPM based mechanism also satisfies the beat-the-quote rule without revealing the buyer's evaluation model to the sellers. This is achieved through the use of reservation levels set as the best bid's achievements augmented by a minimal increment Δ and communicated to the sellers as the minimal requirements. Note that revealing the importance weights still does not reveal completely the buyer's preference model. Thus one may make the attributes importance weights commonly available to meet possible requirement for some public sector procurement auctions.

5 Conclusions

This paper describes a multi-attribute auction mechanism based on reference points with the non-compensatory importance weights for several attributes (criteria). As with the weighted sum model the buyer's preferences include value functions. However, compensatory weights associated with attributes are replaced by aspiration levels that represent the required values on the attributes of the item to be purchased and the non-compensatory importance weights associated with attributes. Similar to the unweighted RPM multi-attribute auction mechanism [3], auctions are conducted using reservation levels that express the minimum values acceptable on the attributes. Since the WOWA aggregation with positive weights is strictly monotonic, this way of defining counterproposal ensures a successive refinement of the best bids in each round and thereby preserves the efficiency of the RPM auction. Thus the mechanism addresses the shortcomings of the weighted sum model while allowing to take into account the importance weighting of several attributes.

Acknowledgment. The research was partially supported by the Polish National Budget Funds 2010–2013 for science under the grant N N514 044438.

References

1. Bapna, R., Goes, P., Gupta, A.: A theoretical and empirical investigation of multi-item on-line auctions. Information Technology and Management 1, 1–23 (2000)
2. Bapna, R., Goes, P., Gupta, A.: Insights and analyses of on-line auctions. Communications ACM 44, 43–50 (2001)
3. Bellosta, M.-J., Brigui, I., Kornman, S., Vanderpooten, D.: A multi-criteria model for electronic auctions. In: ACM Symposium on Applied Computing (SAC 2004), pp. 759–765 (2004)
4. Bellosta, M.-J., Kornman, S., Vanderpooten, D.: An Agent-Based Mechanism for Autonomous Multiple Criteria Auctions. In: Proceedings of the IEEE/WIC/ACM International Conference on Intelligent Agent Technology (IAT 2006), pp. 587–594 (2006)
5. Bichler, M.: An experimental analysis of multi-attribute auctions. Decision Support Systems 29, 249–268 (2000)
6. Bichler, M., Kalagnanam, J.: Configurable offers and winner determination in multi-attribute auctions. Eur. J. Opnl. Res. 160, 380–394 (2005)
7. Chandrashekar, T.S., Narahari, Y., Rosa, C.H., Kulkarni, D.M., Tew, J.D., Dayama, P.: Auction based mechanisms for electronic procurement. IEEE Trans. Automation Sci. 4, 297–321 (2006)
8. Hochner, G., Bichler, M., Davenport, A., Kalagnanam, J.: Industrial procurement auctions. In: Cramton, P., Shoham, Y., Steinberg, R. (eds.) Combinatorial Auctions, pp. 593–612. The MIT Press, Cambridge (2006)
9. Jennings, N.R., Faratin, P., Lomuscio, A.R., Parsons, S., Sierra, C., Wooldridge, M.: Automated negotiation: prospects, method and challenges. Int. J. Group Decision and Negotiation 10, 199–215 (2001)

10. Kameshwaran, S., Narahari, Y., Rosa, C.H., Kulkarni, D.M., Tew, J.D.: Multiattribute electronic procurement using goal programming. Eur. J. Opnl. Res. 179, 518–536 (2007)
11. Krishna, V.: Auction Theory. Academic Press, San Francisco (2002)
12. Lewandowski, A., Wierzbicki, A.P.: Aspiration Based Decision Support Systems – Theory, Software and Applications. Springer, Berlin (1989)
13. Morris, J., Maes, P.: Sardine: An agent-facilitated airline ticket bidding system. 4th International Conference on Autonomous Agents (Agents 2000), Barcelona, Spain (2000)
14. Narahari, Y., Garg, D., Narayanam, R., Prakash, H.: Game Theoretic Problems in Network Economics and Mechanism Design Solutions. Springer, Heidelberg (2009)
15. Nisam, N., Roughgarden, T., Tardos, E., Vazirani, V.V. (eds.): Algorithmic Game Theory. Cambridge University Press, Cambridge (2007)
16. Ogryczak, W.: Preemptive reference point method. In: Climaco, J. (ed.) Multicriteria Analysis — Proceedings of the XIth International Conference on MCDM, pp. 156–167. Springer, Berlin (1997)
17. Ogryczak, W., Kozłowski, B.: Reference Point Method with Importance Weighted Ordered Partial Achievements. TOP(2009) (forthcoming), doi: 10.1007/s11750-009-0121-4
18. Ogryczak, W., Studziński, K., Zorychta, K.: DINAS: A Computer-Assisted Analysis System for Multiobjective Transshipment Problems with Facility Location. Comp. Opns. Res. 19, 637–647 (1992)
19. Ogryczak, W., Śliwiński, T.: On solving linear programs with the ordered weighted averaging objective. Eur. J. Opnl. Res. 148, 80–91 (2003)
20. Ogryczak, W., Śliwiński, T.: On Optimization of the Importance Weighted OWA Aggregation of Multiple Criteria. In: Gervasi, O., Gavrilova, M.L. (eds.) ICCSA 2007, Part I. LNCS, vol. 4705, pp. 804–817. Springer, Heidelberg (2007)
21. Petric, A., Jezic, G.: Reputation Tracking Procurement Auctions. In: Nguyen, N.T., Kowalczyk, R., Chen, S.-M. (eds.) ICCCI 2009. LNCS, vol. 5796, pp. 825–837. Springer, Heidelberg (2009)
22. Teich, J.E., Wallenius, H., Wallenius, J., Zaitsev, A.: A multi-attribute e-auction mechanism for procurement: theoretical foundations. Eur. J. Opnl. Res. 175, 90–100 (2006)
23. Torra, V.: The weighted OWA operator. Int. J. Intell. Syst. 12, 153–166 (1997)
24. Torra, V., Narukawa, Y.: Modeling Decisions Information Fusion and Aggregation Operators. Springer, Berlin (2007)
25. Wierzbicki, A.P.: A Mathematical Basis for Satisficing Decision Making. Math. Modelling 3, 391–405 (1982)
26. Wierzbicki, A.P., Makowski, M., Wessels, J. (eds.): Model Based Decision Support Methodology with Environmental Applications. Kluwer, Dordrecht (2000)
27. Wurman, P.R., Wellman, M.P., Walsh, W.E.: Specifying rules for electronic auctions. AI Magazine 23, 15–23 (2002)
28. Yager, R.R.: On ordered weighted averaging aggregation operators in multicriteria decision making. IEEE Trans. Systems, Man Cyber. 18, 183–190 (1988)